Alternator Health Monitoring For Vehicle Applications

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Report Documentation Page

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14. ABSTRACT
To develop and evaluate methods and algorithms for monitoring and predicting the health of military vehicle components or systems.

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Vehicle Component Health Monitoring Overview

Program Area: Prognostics and Health Monitoring

Objectives: To develop and evaluate methods and algorithms for monitoring and predicting the health of military vehicle components or systems.

Deliverables:

(a) Develop a methodology to monitor and predict the health of a vehicle component or subsystem.

(b) Evaluate algorithms for health monitoring and prognostics for vehicle components.

(c) Technical report which document works and results.

Task #	TASKS
✓ Task 1:	Critical Component Selection
✓ Task 2:	Study Failure Modes
✓ Task 3:	Construct Test-bed to Validate Method
✓ Task 4:	Evaluate Health Monitoring Algorithms
✓ Task 5:	Technical report

(09/20/2007—12/31/2008)

Task#	1	2	3	4	5	6	7	8	9	10	11	12	1	2
Task1	■	■												
Task2			■	■	■	■								
Task3				■	■	■	■	■	■	■	■			
Task4										■	■	■	■	■
Task5													■	■

Budget: 1 GRA, PI support

Industry Mentors:
Joe Gothamy, Ken Fischer, James Bechtel of TARDEC

University:
Professor Jay Lee, Professor Teik Lim

Outline

- Project background
- Alternator failure modes
- Experimental test-bed
- Signal processing and feature extraction
- Health monitoring algorithms and results
- Summary and conclusions

Project Background

•The objectives of the project was to develop and evaluate prognostic and health monitoring algorithms for military vehicle components.

•In order to move forward with this objective, it was necessary for this 1-year study to focus on monitoring the health of a critical component on the vehicle.

•A list of potential components were formed where there would be a benefit for health monitoring and prognostics.

•This list was further narrowed down based on the feasibility, and the vehicle alternator component from the HMMWV vehicle was chosen as the case study for this project.

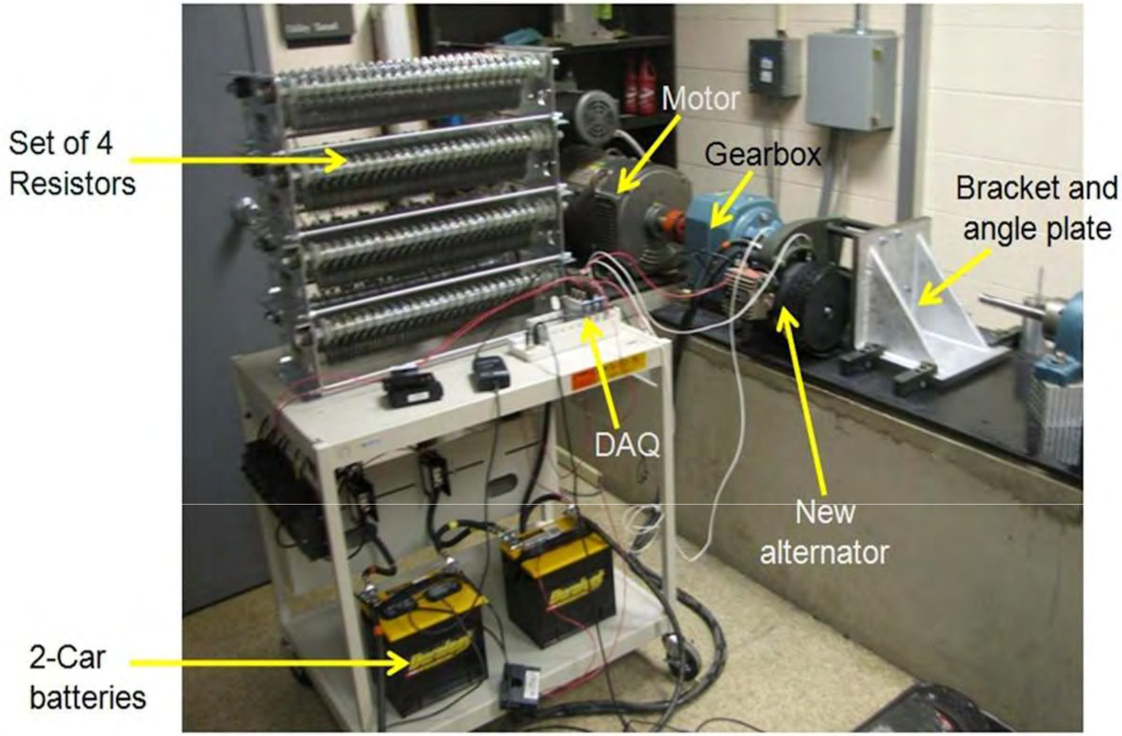
•The health monitoring methods developed will be validated using data collected from a test-bed from a degraded used alternator and a healthy new alternator.

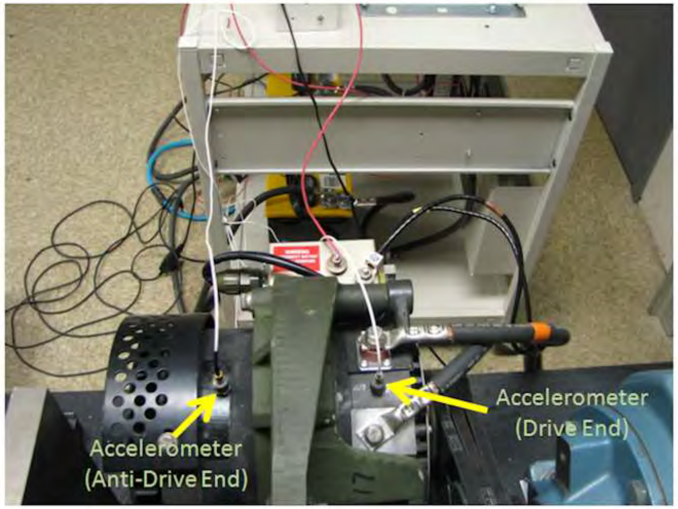
Alternator was chosen

Alternator Failure Modes

Failure Mode	Signals To Measure	Expected Degradation Pattern
Alternator Bearings	Measure vibration signal near drive end and anti-drive end bearing	Greater magnitude at bearing fault frequencies and RMS for degraded component
Alternator Diodes	28V and 14V output voltage signals and current signals	Higher level of ripple and differences in 36^{th} and 72^{nd} voltage harmonics
Alternator Stator Windings	AC current signals and vibration signals	Differences in vibration and current higher order harmonics such as 30^{th} and 36^{th}.

Alternator Test-bed





DAQ Hardware:

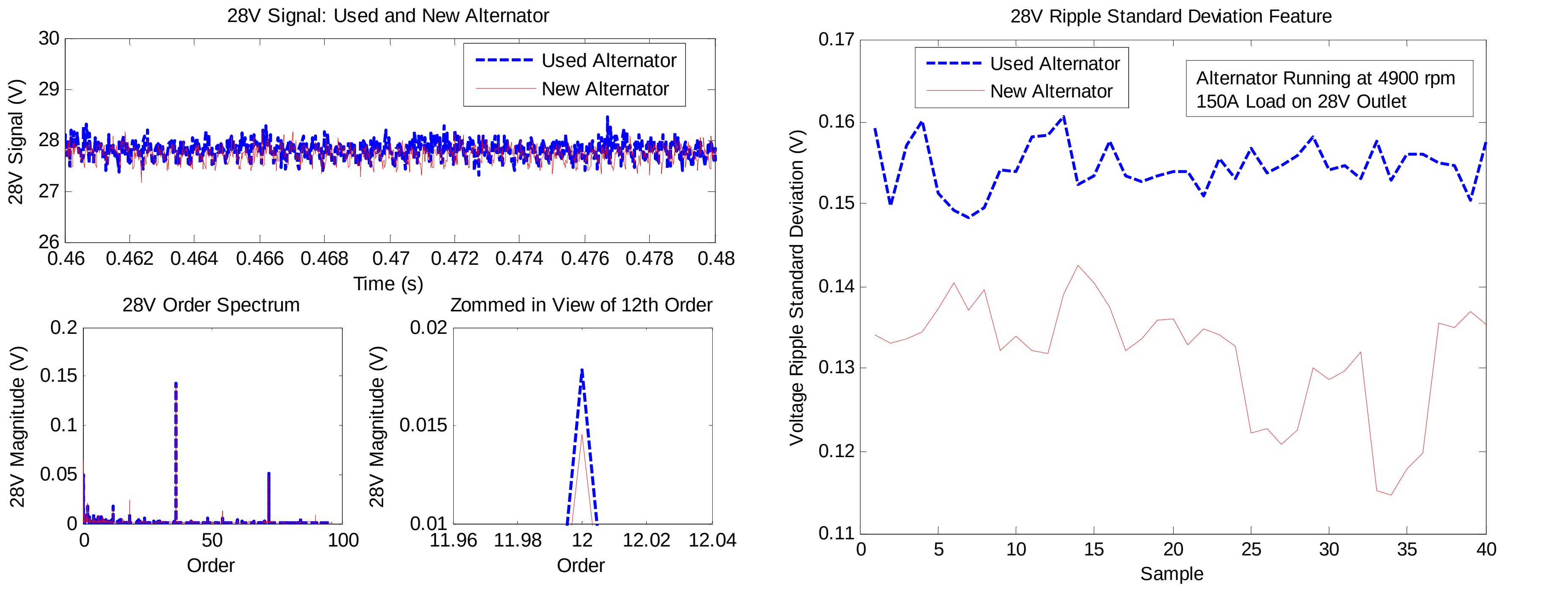
NI Compact DAQ (cDAQ-9172)

1. NI 9215 (for AC current measurement)
2. NI 9221 (Voltage Measurements)
3. NI 9233 (Vibration Measurements)

Measured Signals:

1. AC Current on 28V outlet
2. Alternator Tachometer Signal
3. 28V Outlet Voltage Signal
4. 14V Outlet Voltage Signal
5. DC Current on 14V outlet
6. Vibration near DE Bearing
7. Vibration near ADE Bearing

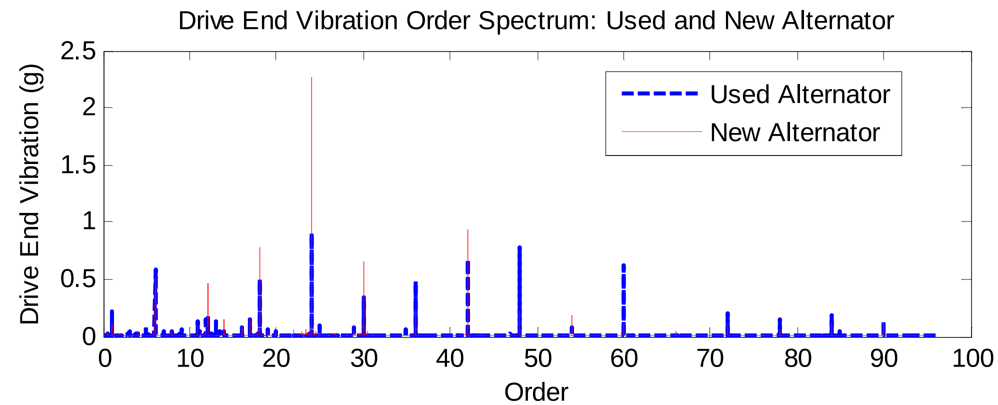
Feature Extraction for Monitoring Alternator Diodes

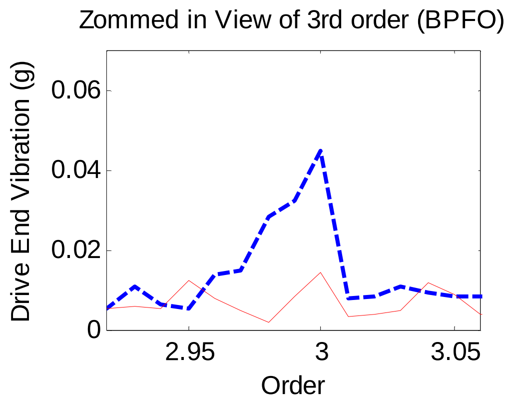


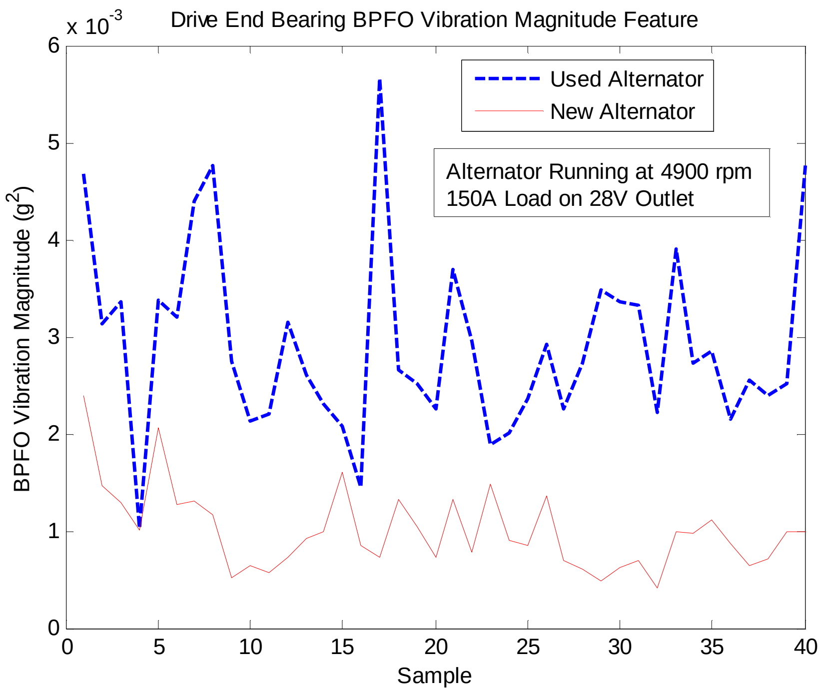
•The 28 voltage time signal and order spectrum are shown, each signal is sampled at a rate of 50KHz due to the 36th and higher harmonics in the signal.

•Larger amount of variation in the 28V ripple signal for the degraded used alternator compared to the healthy new alternator.

Feature Extraction for Monitoring Alternator Bearings

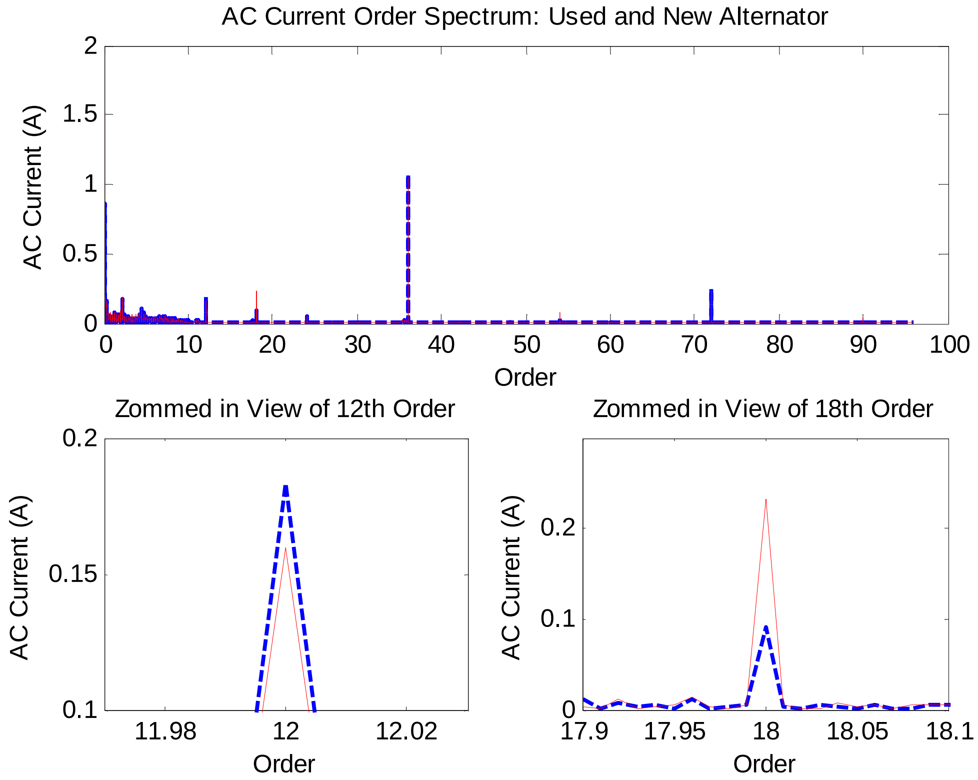


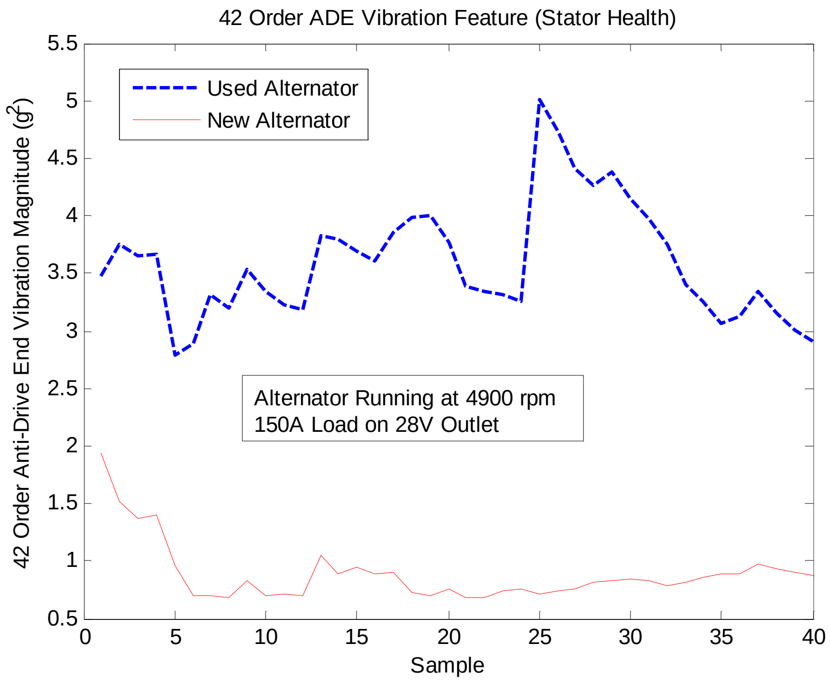




- The degraded used alternator has clear differences in the magnitude in the bearing fault frequencies, such as the amplitude at the BPFO frequency which is associated with a bearing with an outer race damage.

Feature Extraction for Monitoring Alternator Stator Winding





- The degraded used alternator has clear differences in the magnitudes in the high order current and vibration harmonics, such as the 42nd order vibration harmonic.

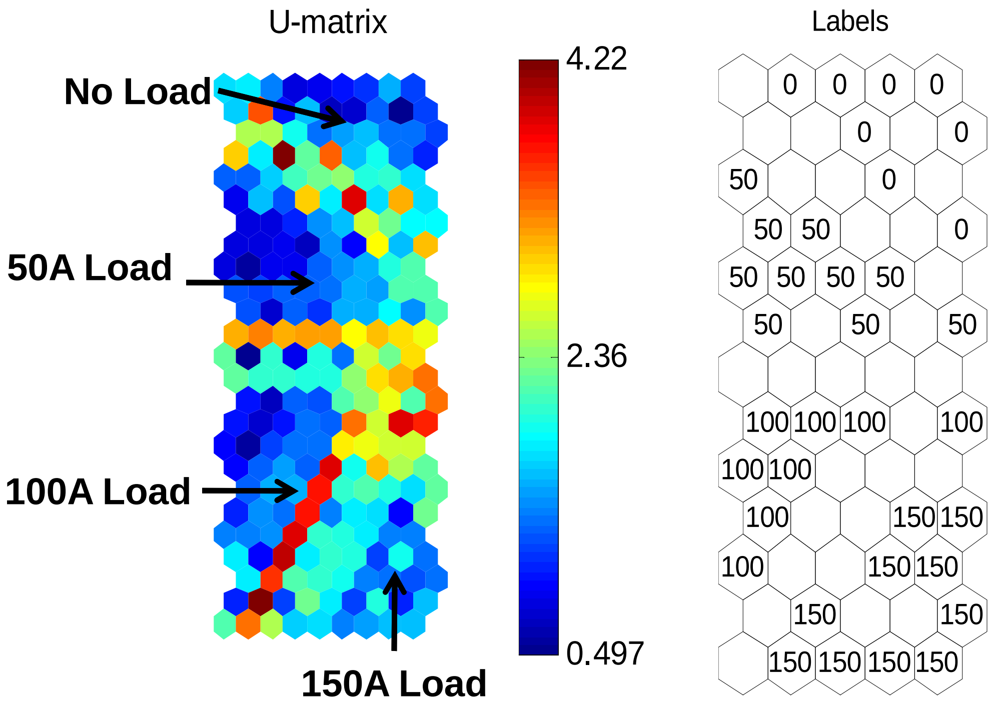
Multi-Regime Aspect

•The used and new alternator were tested under different electrical loads and speeds, 24 different load and speed combinations.

•A self-organizing map (SOM) was used to see whether the data formed clusters based on electrical load or speed.

•As shown for the data when rotational speed was held constant at 4800 rpm, the vibration and electrical data collected at different loads formed clear clusters.

•Similar results were also seen for rotational speed, when electrical load was held constant.



Main Points:

1. Necessary to segment and train for each operating regime.
2. Analyze health monitoring results from data collected in each regime.

Logistic Regression Health Assessment Results

Take Extracted and Selected Features

Features

Sample ↓

RMS	BPFO	BPFI	Temp
1.21	0.457	0.321	23.2
1.25	0.438	0.317	23.8
1.23	0.455	0.321	23.5
1.89	0.898	0.788	28.4
1.97	0.972	0.767	28.9
1.88	0.988	0.792	29.2

Label

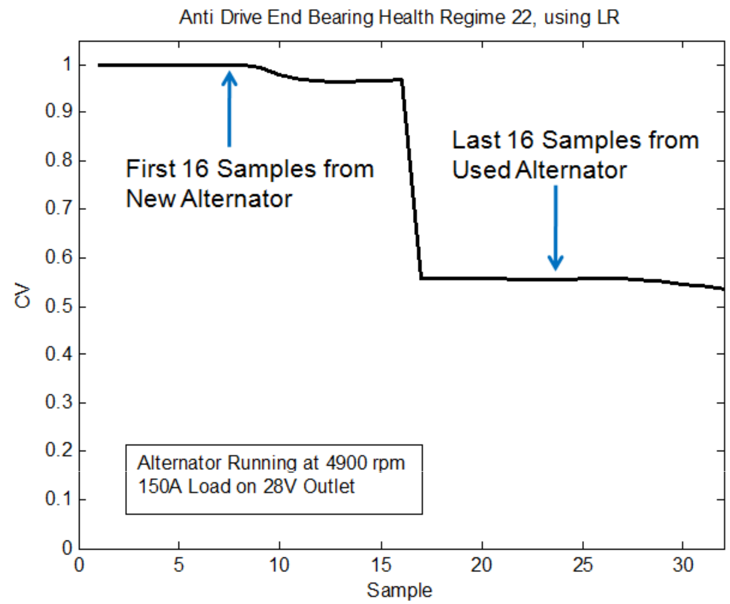
0.95
0.95
0.95
0.05
0.05
0.05

Fit Regression Parameters

Use Trained Model to Calculate Health Value

$$\Pr ob(event) = P(\mathbf{x}) = \frac{1}{1+e^{-g(\mathbf{x})}} = \frac{e^{g(\mathbf{x})}}{1+e^{g(\mathbf{x})}}$$

Results

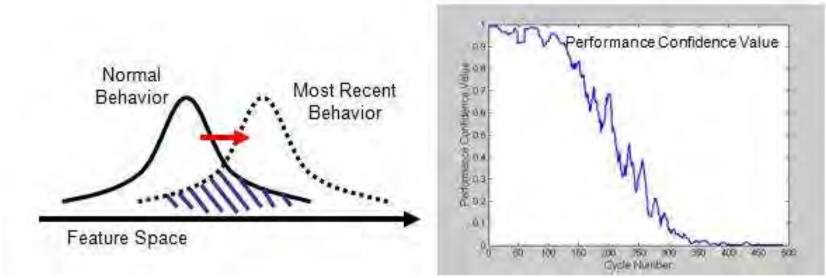


	Quality Results	Type I Error	Type II Error
Ratio	91 of 96	0 of 96	5 of 96
Percent	94.79 %	0.00 %	5.21 %

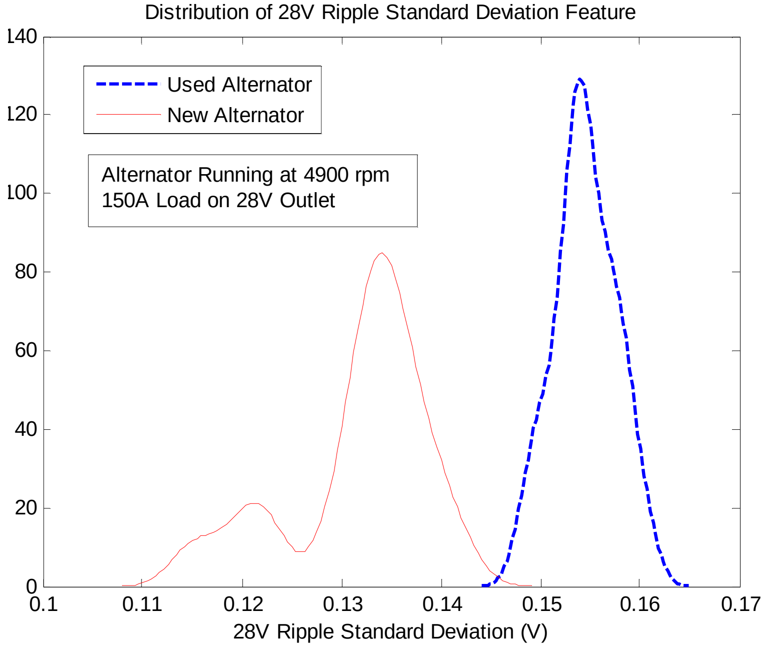
- Overall results using logistic regression were quite good, 5% missed detection.

Statistical Pattern Recognition Health Assessment Results

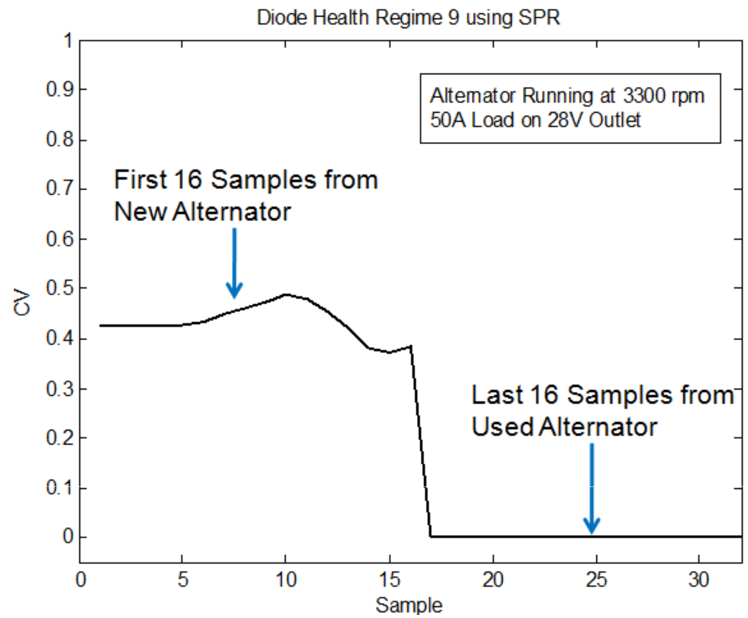
Concept of Statistical Pattern Recognition



Key assumption that features follow normal distribution



Results



- Method can distinguish the healthy new alternator from used alternator but is too sensitive.
- Many features do not follow normal distribution so this algorithm was not considered any further.

Self-Organizing Map-MQE Method Health Assessment Results

Concept of SOM-MQE Method

Train self-organizing map with data from healthy component

↓

New data comes in and best matching unit on map is found

↓

Distance between new data and best matching unit is defined as minimum quantization error (MQE) value

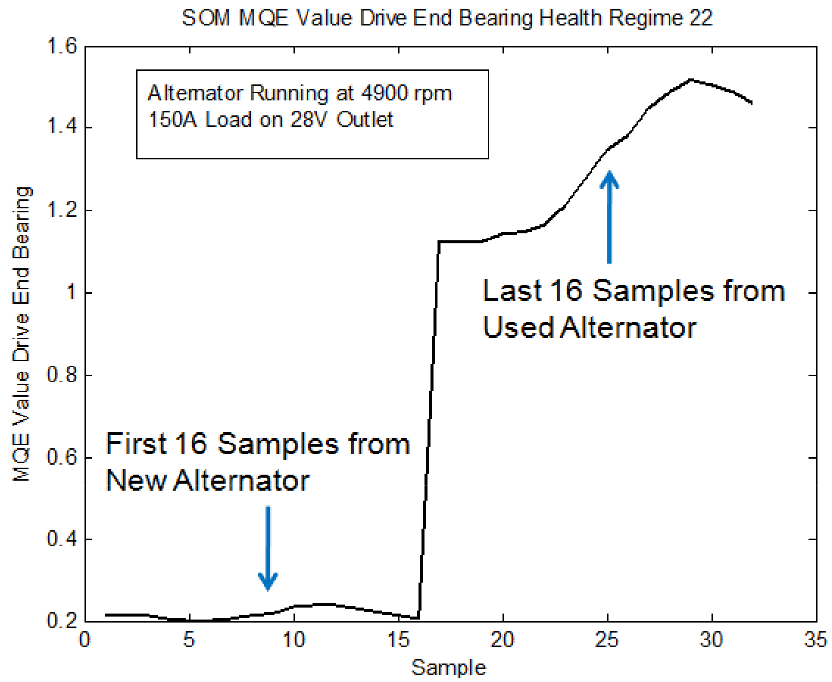
↓

$$MQE = \left\| D - w_{bmu} \right\|$$

↓

MQE value indicates how far from normal the component is, indicates amount of degradation

Results



	Quality Results	Type I Error	Type II Error
Ratio	89 of 96	2 of 96	4 of 96
Percent	92.71%	2.08 %	4.17 %

•Accuracy of health results very close to logistic regression method.

Summary and Conclusions

•Understanding the failure modes and expected failure patterns are the key to the proper signal processing and feature extraction and selection (the features are the inputs to the health monitoring and prognostic algorithms).

•One has to consider the effect of different operating regimes and settings, it is typically necessary to segment the data and train the algorithm for each operating regime.

•In a few operating regimes it might be more difficult to monitor the health, for example at idle speed, monitoring the alternator bearing health was more difficult and it was harder to classify the degraded alternator from the new alternator bearings at idle speed.

•Statistical pattern recognition is based on the assumption of a normal distribution for the features, and if this is not met this algorithm should not be used.

•Both the logistic regression method and self-organizing map method provided similar level of accuracy, however logistic regression is less computationally demanding, so the simpler algorithm is the best option (logistic regression).

Benefits and Impact to Members

Algorithm Development and Evaluation

Evaluation of Health Monitoring Algorithms

↓

Algorithms tested in application with many regimes and variety of signals

↓

Performance accuracy results indicate which algorithm is best.

↓

Impact:
Know which algorithm is most suitable.

PHM Method for Key Components

Developed Method Applicable to Motors and Generators

↓

Machine tools, power plants, vehicles, most any application has a type of motor or generator

↓

Impact
Adaptable methodology for monitoring the health for vehicle alternator is developed and can be used in many applications

Thank

You

Questions?